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# Classification of Brain MRI Tumor Images: A Hybrid Approach

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**Abstract**

Nowadays, brain tumor has been proved as a life threatening disease which cause even to death. Various classification techniques have been identified for Brain MRI Tumor Images. In this paper brain tumor from MR Images with the help of hybrid approach has been carried out. This hybrid approach includes discrete wavelet transform (DWT) to be used for extraction of features, Genetic algorithm for diminishing the number of features and support vector machine (SVM) for brain tumor classification. Images are downloaded from SICAS Medical Image Repository which classified images as benign or malign type. The proposed hybrid approach is implemented in MATLAB 2015a platform. Parameters used for analyzing the images are given as: entropy, smoothness, root mean square error (RMS), kurtosis and correlation. The simulation analysis approach results shows that hybrid approach offers better performance by improving accuracy and minimizing the RMS error in comparison with the state-of-the-art techniques in the similar context.


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Keywords: MRI; Classification; Images; Brain; Tumor

## 1. Introduction

MRI stands for magnetic resonant imaging is an imaging procedure that delivers excellent pictures of the structures which are anatomical in context of the human body, particularly in the cerebrum, gives rich data for clinical analysis and biomedical research. The indicative estimations of MRI are incredibly amplified by the computerized and precise characterization of the MRI pictures. MRI (Magnetic Resonance Imaging) has demonstrated out as an effective instrument in location of brain tumor with the assistance of MR Images. It is a

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non-intrusive strategy which delivers exceptionally point by point 2D and 3D pictures of the organ inside the brain toward each path. As the large amount of information given through MRI system, it is illogical to build up a strategy which can characterize the pictures in typical or strange through human assessment. [2]

Brain Tumor is a bunch of abnormal cells developing in the brain. It might happen in any individual at any age and show up at any area and have wide assortments of shapes and sizes. They can be dealt with by radiotherapy or by chemotherapy. This turns out to be a severe problem which causes even death. Tumor is additionally classified in two: malignant and benignant. Benignant tumors have homogeneous structure and don't contain disease cells while malign have heterogeneous structure and contain malignancy cells. Benign tumors are either radio-logically or surgically crushed and have uncommon odds of become back. Malignant are life undermining tumor and can be dealt with by chemotherapy, radiotherapy or their blend. In order to deal with brain tumor, MRI is a useful technique which provides us all fine details of brain such that we can easily detect the area of tumor.

Data mining helps up to a greater extent to face out with such fine details. As SVM turns out be the best approach in order to deal with detection of tumor [17, 18] , we analyze some brain images with the techniques SVM , PCA and DWT obtained from SICAS Medical Image Repository.

## 2. Literature Review

S. Chaplot et al. [2] proposed a novel strategy for the classification of magnetic resource images of human brain which utilizes wavelets as contribution to support vector machine and neural system self-organizing maps. The proposed technique orders MR brain images as abnormal or normal. Their proposed approach has a dataset of 52 MR brain images. A rate of over 94% was achieved with the self-organizing maps (SOM) whereas and 98% using the support vector machine method. It was observed that the classification rate is high for a support vector machine classifier if compared with a self-organizing map-based approach.

M. Maitra et al. [3] proposed new approach for mechanized diagnosis, for the classification of MRI images. The proposed strategy is seemingly a variant of orthogonal discrete wavelet transform (DWT), called Slantlet transform for highlight extraction. Here, a 2-D MR picture processes its intensity histogram and then connected to Slantlet transform as its histogram flag. At that point an element vector is made by considering the sizes of Slantlet transform yields comparing to six positions which are supposed to be spacial, picked by a particular rationale. The components which are extricated used to prepare a neural system based classifier. The fundamental reason for classifier is to arrange the pictures either as typical or unusual for Alzheimer's sickness. From this strategy, they accomplished the productivity of 100% in accurately characterizing the Alzheimer's malady.

Y. Zhang et al. [4] proposed a hybrid technique in light of forward neural network (FNN) to group MR brain images. The proposed strategy initially utilized the discrete wavelet transform in order to extract main features from MR Images and after that applied the principal component analysis technique to diminish feature space to a limit. The diminished components were sent to a forward neural network (FNN), where the parameters were upgraded utilizing an improved artificial bee colony algorithm (ABC) calculation in view of both fitness scaling and chaotic theory.. At that point, K-fold cross validation technique was utilized to maintain a strategic distance from over fitting. The outcomes demonstrate that SCABC can acquire the minimum mean MSE and 100% accuracy.

JankiNaik et al. [6] introduced a proposed method to classify the medical images for diagnosis. Here, pre-processing, feature extraction, association rule mining and classification are the steps involved. Some experiments with MRI images for tumor detection is carried out here. Preprocessing has been done with the help of median filtering process. After that, essential features have been extracted with texture feature technique. Then mining of association rules is done from extracted feature using Decision Tree classification algorithm. They concluded that the proposed method improves the efficiency of classification of CT scan images than traditional methods.

Y. Zhang et al. [17] proposed a novel method for classify brain MRI images as either normal or abnormal by using SVM and DWT (Discrete Wavelet Transform) approach. PCA (Principal Component Analysis) approach also used to diminish the no. of features extracted by Wavelet Transform. These methods were applied on 160 MR Brain Images for detection of Alzheimer's disease with four different kernels and achieved maximum accuracy for GRB kernel of 9.38%.

## 3. Technology Used

### *3.1 Support Vector Machine (SVM)*

SVM is classified as the most powerful classification algorithm which is capable of giving higher performance in terms of accuracy as compared to other classification algorithms. SVM is used for classification of both linear and non-linear type of data. This classifier is developed from statistical learning introduced by Vipnik in 1992. SVM classifier identifies the problem by finding out the hyper-plane with largest margin, i.e. maximal marginal hyper-plane. SVM has the special property of simultaneously minimizing the classification error and maximizing the geometric margin. For the non-linear data, it maps the input vector into a higher dimensional space where a maximal hyperplane is built. By transforming it into high dimensional space, it searches for linear optimal separating hyper-plane with the help of support vectors and margins [20]. Fig 1 [19] shows SVM topology in hyperspace:

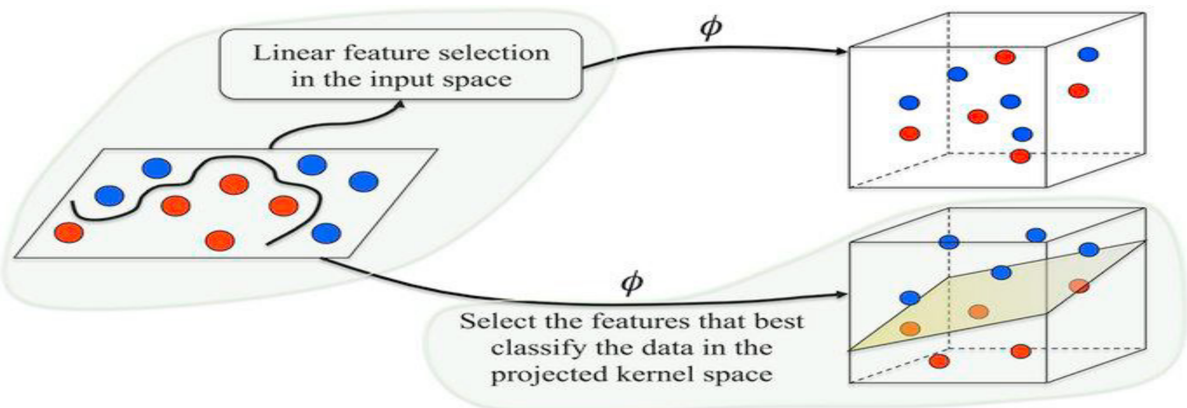



Fig. 1. Nonlinear SVM Topology in hyper plane

For handling different types of data located at many sides of a hyper-surface, kernel strategy is used with SVMs. In this, every dot product is changed with non linear kernel function [22]. In this paper, we will deal with three type of kernels: linear kernels, polynomial kernels and RBF (Radial Basis Function) Kernels.

### *3.2 Genetic algorithm (GA)*

Genetic algorithm (GA) is a meta-heuristic algorithm which is inspired by natural selection. This natural selection further belongs to superset of evolutionary algorithms (EA). Genetic algorithms provide solutions to search and optimization and problems. These algorithms depend upon bio-inspired operators. These operators are crossover, mutation, and selection etc apart from defining the optimization function. The genetic algorithm begins with initialization of population which is an iterative process. The iteration is referred to as a generation and in each such generation; the fitness is evaluated corresponding to each individual. In the optimization problem, the fitness reflects the value of the objective function in the optimization problem.

*3.3 Discrete Wavelet Transform (DWT)*

First, Discrete Fourier Transform is used as signal analysis tool which decompose a signal into different sinusoidal signals of different frequencies, i.e. from time domain to frequency domain signals. But it has disadvantage of rejecting the time information of signal [21]. To overcome this drawback, Discrete Wavelet Transform (DWT) is used which decompose the signal into mutually orthogonal wavelet functions. It preserves the frequency and time domain in association with the signal.

## 4. Proposed Methodology

MRI Brain Images downloaded from Medical Image Repository are present in .mha format. To deal with .mha image files, READ MEDICAL DATA 3D is needed to attach with MATLAB tool. Then, it is converted to jpeg extension images. Then, DWT transformation is applied to the image for the extraction of the features. But the no. of features are so much large such that we have to reduce the features by applying Principal Component Analysis (PCA) technique. These are the phases introduced in the Preprocessing phase. After that, Kernel SVM classifier is built which is required for classifying images as normal or abnormal. Fig. 2 shows the flow chart of proposed work done.

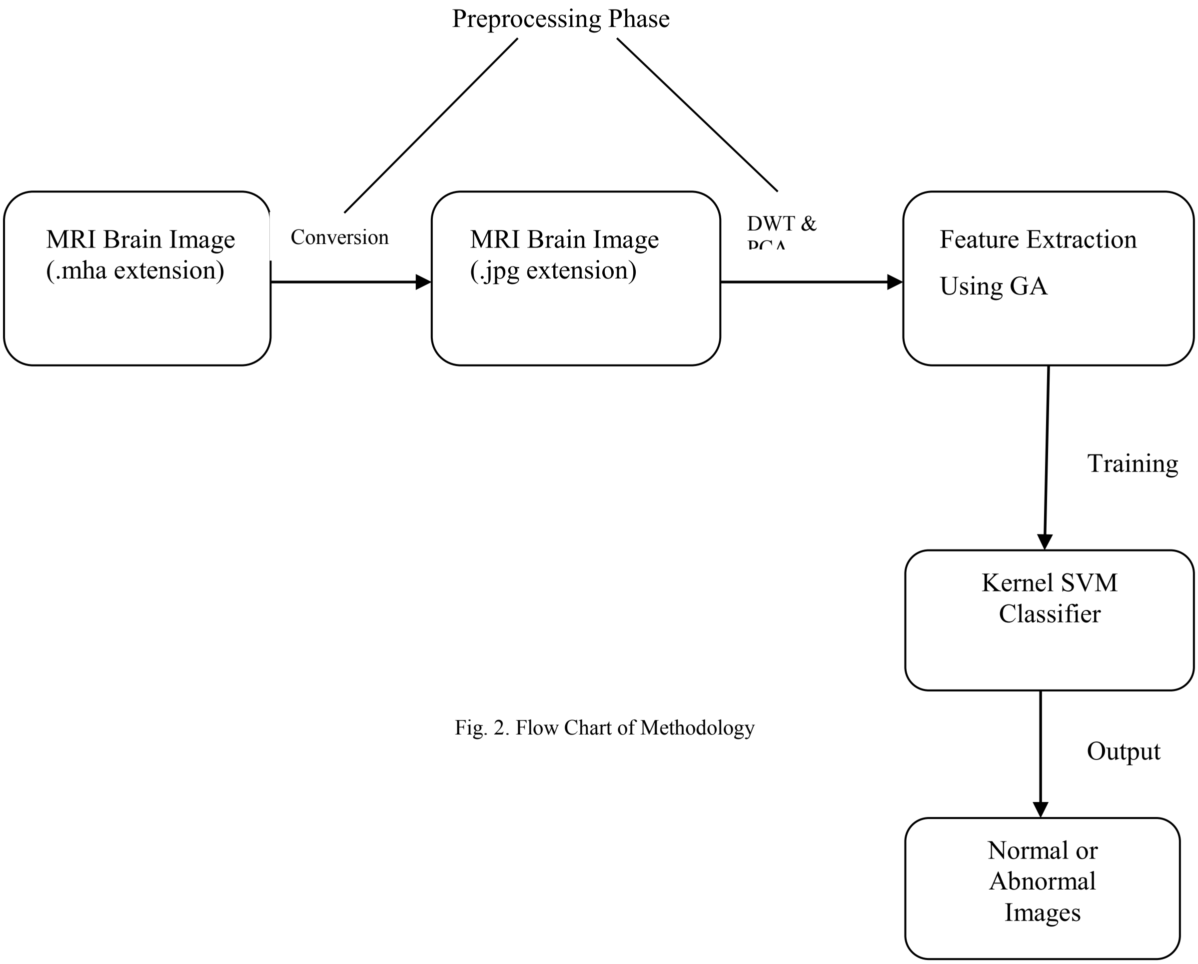
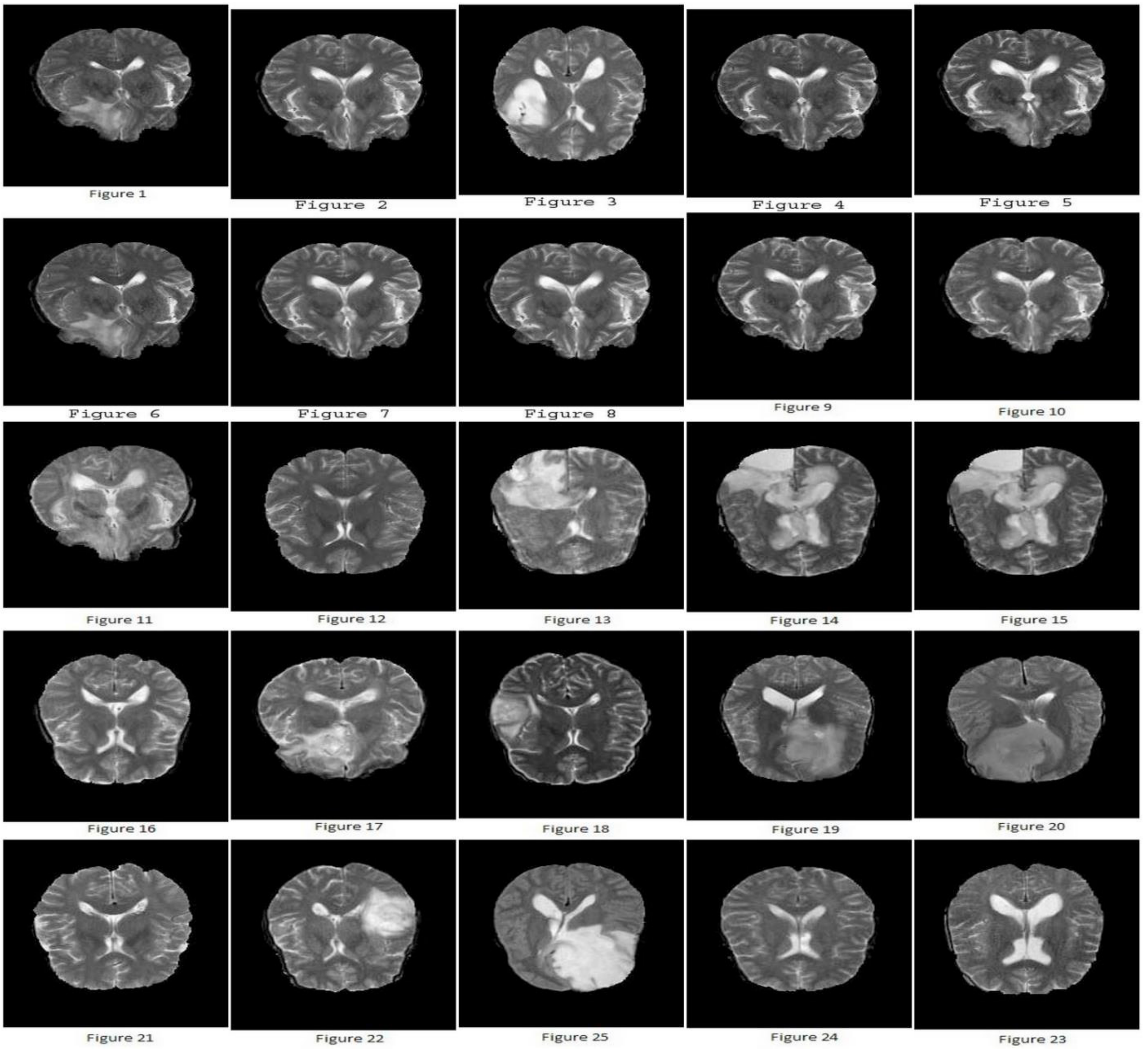



Fig. 2. Flow Chart of Methodology

## 5. Input Image Data Source

For analyzing the described technique, images dataset are obtained from SICAS Medical Image Repository. A data set of 25 MRI Brain Images (20 benign, 5 malign images) given in the picture1 which are the T2 weighed axial view of the brain images.




Picture1: Dataset of 25 Brain MR Images.

## 6. Results

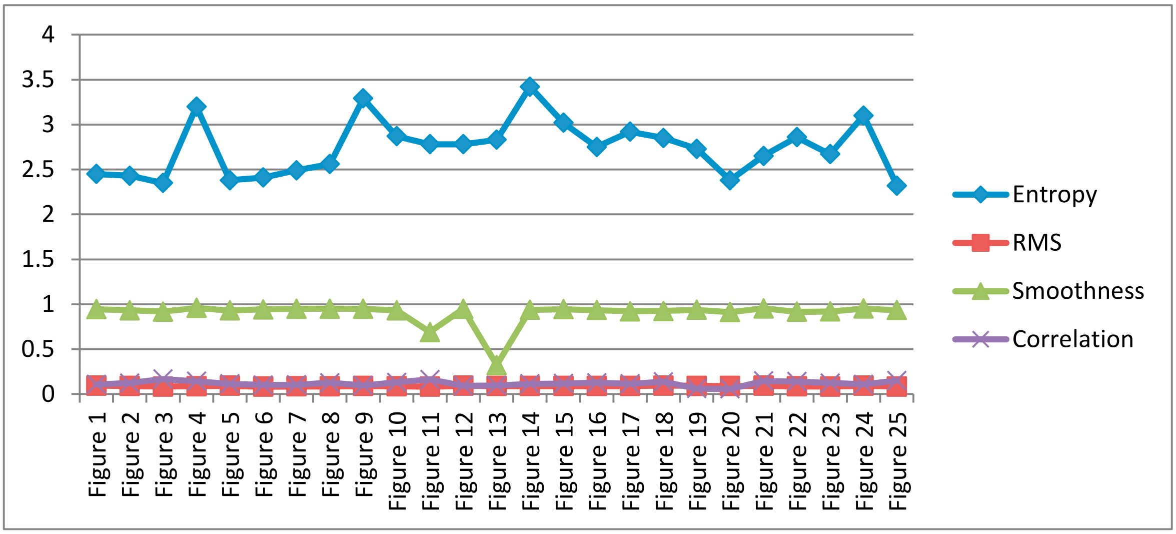
Table1 shows the picture wise result of the MR Images on the behalf of the following parameters: Type of tumor, Entropy, RMS, Smoothness, Kurtosis and Correlation. Type of tumor parameter has two values: benign and malign. Out of there 25 images, 20 are classified as benign and 5 are as malign. RMS represents root mean square error which computes RMS value of every row and column's input. From Table 1, RMS value is near to 0.1.

Smoothness describes as the measure of different grey level that can be utilized to build up descriptors of relative smoothness. For Figure 13 and Figure 11, its value is 0.322 and 0.60 which is very low. For other images, it is near to 1 which shows smoothness. Entropy defines the randomness which describes the text part of the input image, i.e. distribution variation within a image. Kurtosis shows the flatness of a distribution region to a normal region. Its value varies from 6 to 29. Correlation defines how a pixel correlate to its neighbor pixel. Its value varies from -1 to 1. For negative correlated image, it is -1 and for positive, 1. As observed from table, its value is approx. to 0.1.

Linear accuracy varies from 80% to 90%.

Table1: Parameter wise result of MR Images

| MRI Image | Type of Tumor | Entropy | RMS | Smoothness | Kurtosis | Correlation | Linear Accuracy in % |
|---|---|---|---|---|---|---|---|
| Figure 1 | Benign | 2.45 | 0.0938 | 0.944 | 15.97 | 0.107 | 87.4 |
| Figure 2 | Benign | 2.43 | 0.0898 | 0.932 | 24.28 | 0.123 | 89.2 |
| Figure 3 | Benign | 2.35 | 0.0845 | 0.918 | 25.11 | 0.168 | 90.5 |
| Figure 4 | Malign | 3.20 | 0.0868 | 0.959 | 12.24 | 0.142 | 90.7 |
| Figure 5 | Benign | 2.38 | 0.0924 | 0.930 | 28.92 | 0.114 | 87.5 |
| Figure 6 | Benign | 2.41 | 0.0812 | 0.943 | 26.24 | 0.102 | 82.5 |
| Figure 7 | Benign | 2.49 | 0.0856 | 0.948 | 25.05 | 0.103 | 85.2 |
| Figure 8 | Benign | 2.56 | 0.0852 | 0.951 | 24.21 | 0.126 | 91.2 |
| Figure 9 | Benign | 3.29 | 0.0898 | 0.949 | 9.76 | 0.096 | 90 |
| Figure 10 | Benign | 2.87 | 0.0882 | 0.933 | 16.60 | 0.131 | 85.2 |
| Figure 11 | Benign | 2.78 | 0.0821 | 0.690 | 14.54 | 0.162 | 83.2 |
| Figure 12 | Benign | 2.78 | 0.0922 | 0.949 | 15.12 | 0.092 | 89.2 |
| Figure 13 | Benign | 2.83 | 0.0898 | 0.322 | 13.15 | 0.097 | 90.8 |
| Figure 14 | Malign | 3.42 | 0.0888 | 0.937 | 7.15 | 0.114 | 90.1 |
| Figure 15 | Malign | 3.02 | 0.0891 | 0.945 | 13.18 | 0.117 | 90.2 |
| Figure 16 | Benign | 2.75 | 0.0898 | 0.935 | 12.99 | 0.127 | 90.5 |
| Figure 17 | Benign | 2.92 | 0.0898 | 0.922 | 13.26 | 0.114 | 90.9 |
| Figure 18 | Benign | 2.85 | 0.0952 | 0.926 | 10.42 | 0.138 | 88.2 |
| Figure 19 | Benign | 2.73 | 0.0902 | 0.938 | 17.60 | 0.060 | 82.2 |
| Figure 20 | Benign | 2.38 | 0.0898 | 0.913 | 23.48 | 0.057 | 80 |
| Figure 21 | Malign | 2.65 | 0.0921 | 0.954 | 13.32 | 0.146 | 89.2 |
| Figure 22 | Benign | 2.86 | 0.0852 | 0.917 | 11.92 | 0.139 | 90.8 |
| Figure 23 | Benign | 2.67 | 0.0832 | 0.919 | 16.44 | 0.123 | 90.2 |
| Figure 24 | Malign | 3.10 | 0.0922 | 0.952 | 11.11 | 0.109 | 90.9 |
| Figure 25 | Benign | 2.32 | 0.0836 | 0.935 | 19.76 | 0.149 | 90.2 |




Graph1: Graphical representation of Table 1

## 7. Conclusion

The proposed hybrid approach was applied to brain MRI Images in order to classify brain tumor either as benignant or malignant. Automatic brain tumor detection approach reduces the manual labeling time and avoid the human error .This approach is a combination of DWT (Discrete Wavelet Transform) used for feature extraction, then the principal component analysis (PCA) for diminish the features and for the classification of MR images the Support Vector Machine has been used. In future, an enhancement can be further done for optimizing the accuracy and lower down the RMS error rate.

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